Optimal Off-Line Trajectory Planning for Load Ramping of Hybrid Fuel Cell/Gas Turbine Power Generating Plants

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Abstract

The control strategy of Fuel Cell/Gas Turbine Hybrid power plants plays a significant role in maximizing system performance as well as ensuring the protection of equipment for maximum plant life. The primary objective of this paper is the development and solution of a dynamic optimization framework for Fuel Cell/Turbine Hybrid power plants. Optimal control of load changes requires optimal dynamic scheduling of setpoints and feedforward control moves for the system's controllers. Based on a dynamic Simulink model, a modular and flexible AMPL/IPOPT optimization framework that is easily adaptable to different scenarios and/or process flow diagrams has been developed. Using this framework, dynamic optimizations for various scenarios, such as increasing and decreasing load changes at different rates have been performed.

Introduction

The dynamic operation and control of Fuel Cell/Gas Turbine (FC/GT) Hybrid power plants requires a synergy of operation among subsystems, increased reliability of operation, and reduction in maintenance and downtime. The control strategy plays a significant role in system stability and performance as well as ensuring the protection of equipment for maximum plant life [1]. The main goal of this study is to develop and implement a dynamic optimization framework for FC/GT power generating plants. Optimal control of load changes requires dynamic scheduling of setpoints and feedforward control moves for the system's controllers. To build feedforward action into the conventional proportional plus integral based feedback control, a technique is used where, given a desired load profile P_d, the setpoints and feedforward control signals are found via dynamic optimization [2].

Figure 1 shows the internally reforming Direct FuelCell/Turbine (DFC/T) system selected for this study. This system can be divided into two subsystems: the molten carbonate fuel cell system shown on the top and the open and externally heated gas turbine system shown on the bottom. Fresh air is compressed, heated in two stages, and then expanded in the gas turbine. Purified water humidifies natural gas and is pre-heated to anode inlet conditions. Methane is reformed in the fuel cell and its chemical potential is converted to electrical energy. The anode exhaust, which contains some unreacted fuel, is mixed with the turbine exhaust and sent to a catalytic oxidizer. Before being sent to the cathode, the hot oxidizer exhaust passes through a high temperature recuperator (HTR) that heats the compressed air to turbine inlet conditions.

Cathode exhaust, after preheating the anode inlet, preheats the compressed air and finally provides heat to evaporate water in the humidifier.

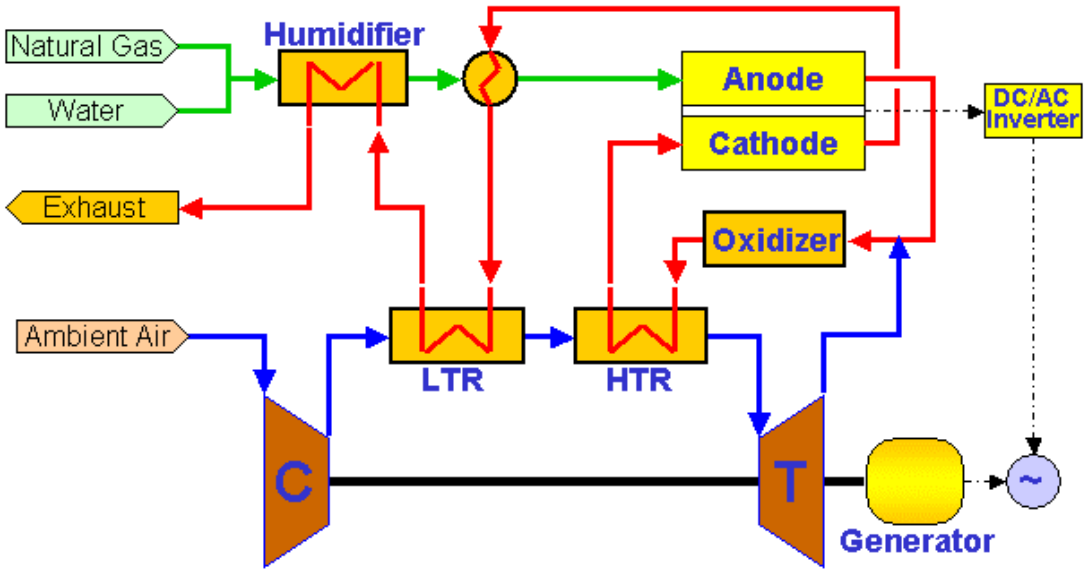

Figure 1: Atmospheric DFC/T hybrid process.

The base system has been modeled in MATLAB and Simulink via dynamic lumped capacitance models. As this is a truly large-scale optimization problem, this model is reformulated in AMPL [3,7], a mathematical programming modeling language well suited for such problems. AMPL also provides the necessary first and second derivatives which aid in convergence of nonlinear programming (NLP) solvers. The specific NLP solver that we will use for dynamic optimization studies is the interior point solver IPOPT [4]. The main reason for choosing IPOPT over an active set sequential quadratic programming (SQP) solver is that this power generation system has numerous inequality and bound constraints, and the number of such constraints increases with finer discretization. This necessitates the use of an interior point solver which overcomes the combinatorial bottleneck of choosing the correct active set. IPOPT is a state-of-the-art interior point NLP solver that has been tested extensively. It can also be tailored to handle complementarity constraints which arise in the actuator and the heat exchanger units.

We will also present ways of handling numerical difficulties that are frequently encountered in such systems. Some of these include consistent reformulation of index-2 differential algebraic equations that arise through chemical equilibrium constraints in the stack model, complementarity constraints that arise in modeling saturation blocks (e.g., actuator output is constrained to [0,1]) and heat exchangers (via number of transfer units formulations), and numerical schemes suited for stiff differential equations. The problem formulation is discretized via orthogonal collocation at Radau points. This is known to handle stiff differential equations well. Recently we have proved that approximations of optimal control problems using Radau collocation converge rapidly to the true solution as the discretization size is made finer [5]. As the models deal with quantities of different magnitudes (e.g. compositions, temperature, enthalpies), scaling is necessary for efficient optimization.

We set up generalized optimization models in AMPL for specified dynamic load changes at a given rate. The optimization is constrained by plant dynamics, as well as input and output restrictions. For the optimization purposes, some of the process's actual controllers are open loop. The control moves and outputs are determined by the optimizer, and then used as feedforward control moves and setpoints for the individual control loops. The objective of the optimization is to minimize the deviations of the control move and output from the desired values. The desired setpoint trajectory for the net plant power is a function of time.

Using this framework, optimization is performed and feedforward control moves and setpoints are scheduled based on the off-line optimization results. The final aim is to create a database of load change trajectories. We will present a case study that demonstrates that this work can facilitate optimal trajectories for closed loop control.

Optimization Model

The dynamic models' differential algebraic equations (DAEs) were discretized using Radau collocation. Using the method of Mattson and Soderlind [8], the stack and preconverter models were reformulated from an index-2 DAE system to an index-1 DAE with consistent initial conditions. The reformulation method is summarized next.

The DAE system of the stack model (mass and energy balances) is given by:

$$M(y,t)\frac{dy}{dt} = f(y,t) \tag{1}$$

where

$$M = \begin{bmatrix} N_c I & & & & \\ & 1 & & & \\ & & N_a I & & \\ & & & 0 & \\ & & & & 0 \end{bmatrix}, \quad y = \begin{bmatrix} x_c \\ T \\ x_a \\ r_1 \\ r_2 \end{bmatrix}, \quad f = \begin{bmatrix} f_c \\ f_T \\ f_a \\ K_1 x_{a,2} x_{a,5} - x_{a,3}\left(x_{a,1}\right)^3 P^2 \\ K_2 x_{a,3} x_{a,5} - x_{a,4} x_{a,1} \end{bmatrix} \tag{2}$$

where N_a and N_c are the anode and cathode molar flowrates, respectively, x_a and x_c are the anode and cathode mole fractions vectors, respectively, K_1 and K_2 are the equilibrium constants for the reformation and water gas shift reactions, respectively, T is the absolute temperature, and P the absolute stack pressure.

The first step in the reformulation is the introduction of new algebraic variables:

$$\bar{y} = \frac{dy}{dt}$$

This transformation converts the above system to an algebraic equation:

$$M(y,t)\bar{y} = f(y,t) \tag{3}$$

The two algebraic rate equations r_1 and r_2 in (2) are differentiated with respect to the absolute temperature T

$$\frac{dK_1}{dT}\bar{T}x_{a,2}x_{a,5} + K_1\bar{x}_{a,2}x_{a,5} + K_1x_{a,2}\bar{x}_{a,5} - \left[\bar{x}_{a,3}\left(x_{a,1}\right)^3 + 3x_{a,3}\left(x_{a,1}\right)^2\bar{x}_{a,1}\right]P^2 = 0 \qquad (4)$$

$$\frac{dK_2}{dT}\bar{T}x_{a,3}x_{a,5} + K_2\bar{x}_{a,3}x_{a,5} + K_2x_{a,3}\bar{x}_{a,5} - \bar{x}_{a,4}x_{a,1} - x_{a,4}\bar{x}_{a,1} = 0 \qquad (5)$$

and are added to the algebraic system (3). Because two equations were added, two other equations need to be eliminated, e.g., from the anode mass balance. In this case, the equations for hydrogen and methane, $x_{a,1}$ and $x_{a,2}$, were eliminated from the set of equations (3). These quantities can be calculated directly from the algebraic equations. A new set of variables are defined by the following equations:

$$z = \begin{bmatrix} x_c \\ T \\ w \end{bmatrix},\ w = \begin{bmatrix} x_{a,3} \\ \vdots \\ x_{a,7} \end{bmatrix} \text{ and } \bar{w} = \begin{bmatrix} \bar{x}_{a,3} \\ \vdots \\ \bar{x}_{a,7} \end{bmatrix},\ \bar{z} = \begin{bmatrix} \bar{x}_c \\ \bar{T} \\ \bar{w} \end{bmatrix} \qquad (6)$$

resulting in a set of differential equations:

$$\frac{dz}{dt} = \bar{z}$$

The initial conditions for the differential variables, $z(0)$, can now be set independently and the algebraic variables, r_1, r_2, $x_{a,1}$, $x_{a,2}$ and $\bar{y}$ can be solved from (3) – (5).
To make the DAE system consistent with the constraint of

$$\sum_{i=1}^{7} x_{a,i} = 1,$$

$x_{a,3}$ is obtained from

$$\sum_{i=1}^{7} x_{a,i} = 1$$

In turn, a third equation (mass balance ODE for $x_{a,3}$) was eliminated.

To improve the calculation efficiency and accuracy in AMPL, the DAE system is scaled using the following techniques:

1. The models consist of different variables of varying scales. To facilitate convergence of the optimization routine to meaningful values, the variables and the constraints had to be scaled. Instead of using individual scaling factors, all variables and constraints of the stack, catalytic oxidizer, and pre-converter models were scaled using a single scaling factor θ

$$T_{out,scaled} = \frac{T_{out}}{\theta},\ h_{scaled} = \frac{h}{\theta},\ Cp_{scaled} = \frac{Cp}{\theta},\ \dot{x}_{out,scaled} = \theta\left(\frac{d\left(x_{out,pc}\right)}{dt}\right) \qquad (7)$$

   where θ=1000, h is the enthalpy, and Cp is the heat capacity.

2. Because K_1 and K_2 are very small in magnitude, a logarithmic formulation is used for efficient numerical calculations. Rather than K_1 and K_2, their logarithms are used as variables:

$$logx_{a,1} = \ln K_2 + logx_{a,3} + logx_{a,5} - logx_{a,4} \qquad (8)$$

$$logx_{a,2} = -\ln K_1 + 3\left(\ln K_2\right) + 4\left(logx_{a,3}\right) + 2\left(logx_{a,5}\right) - 3\left(logx_{a,4}\right) + 2\left[\log\left(P\right)\right] \qquad (9)$$

Problem Definition

With the AMPL models in place, the next step is dynamic optimization. The optimization model was used to track a 90 kW zigzag power ramp from the nominal 300 kW down to 210 kW within 30 minutes and then back up to the nominal operating point.

To achieve these desired trajectories, four conventional PI control loops of the DFC300/T simulation are opened and the corresponding manipulated variables are determined via dynamic optimization: Stack current density, high temperature recuperator (HTR) and oxidizer bypass fractions, and micro turbine terminal voltage. The bypass fractions are bounded between zero and one, where zero means that the unit is completely bypassed and one means that all flow passes through the unit.

The objective function is a minimization of the power tracking error. Auxiliary terms in the objective function force the control variables to be constrained within each temporal mesh. A 2-point collocation scheme is used for discretization.

Results

Figure 2 shows the total system and the stack power as well as the normalized current density. Current density is the input with the biggest impact on the stack power. During the power down-ramp there is an initial offset caused by improper initialization. During the power up-ramp these offsets disappear and the desired total power setpoint ramp is tracked perfectly. Stack power closely follows the current density while turbine power shows the same trends as the oxidizer temperature.

Figure 3 shows on the left the temperature profiles of stack and cathode inlet as well as the HTR bypass fraction which has the biggest influence on the cathode inlet temperature. The dotted lines are the allowable bounds on the cathode inlet temperature. On the right, the oxidizer temperature and the oxidizer bypass valve trends are shown. As the bypass valve closes, the temperature goes up. This trend correlates with the turbine power because a higher oxidizer temperature results in a higher turbine inlet temperature and therefore a higher turbine power.

Figure 4, finally, shows the micro turbine speed and its normalized control variable. The drop in turbine speed at 30 minutes results in an increased power output. This is due a maximum in the power vs. speed characteristic of the micro turbine at low turbine inlet temperatures. At high turbine inlet temperatures, the power monotonically increases with speed.

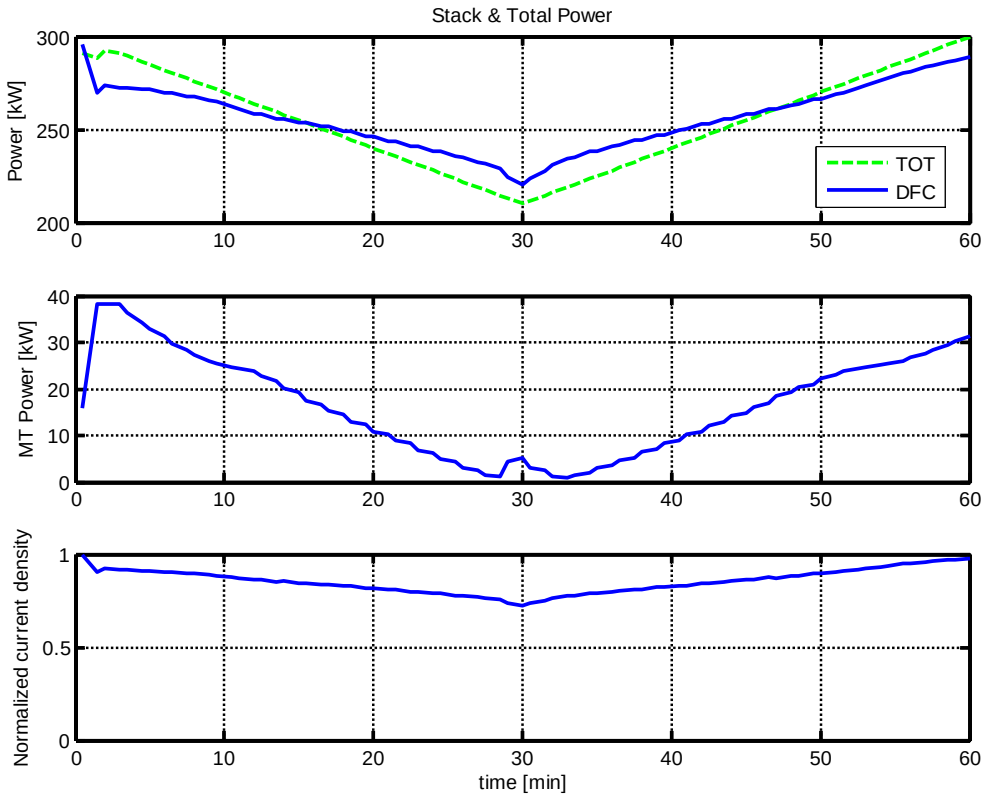

Figure 2: Stack, turbine, and system power vs. normalized current density.

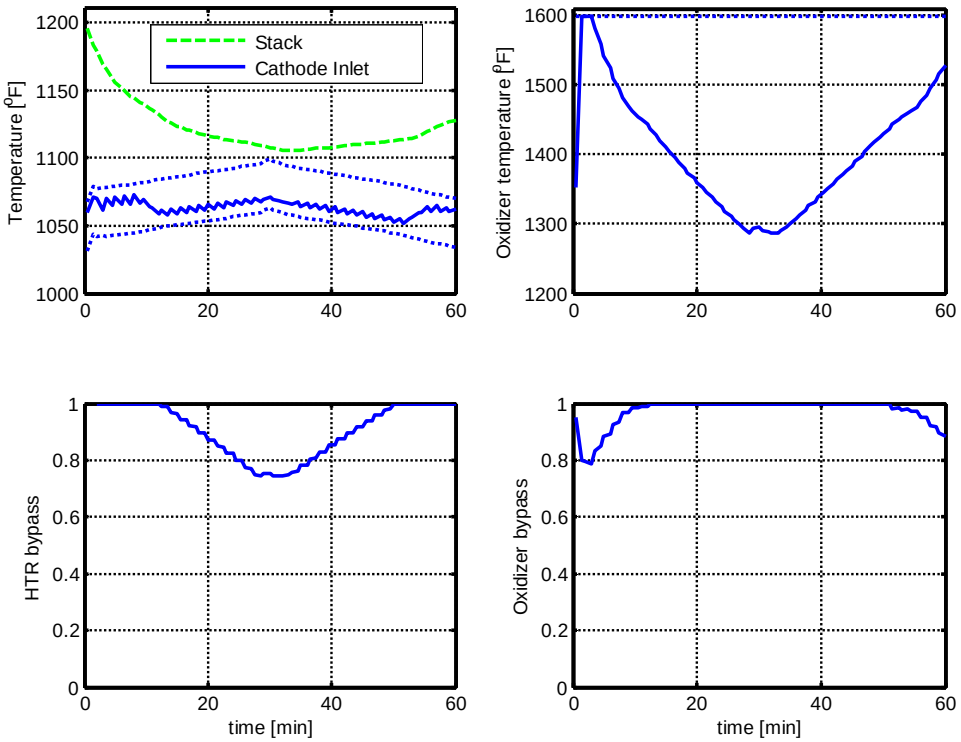

Figure 3: Left: Stack and cathode inlet temperature vs. high temperature recuperator bypass fraction. Right: Oxidizer temperature vs. oxidizer bypass fraction.

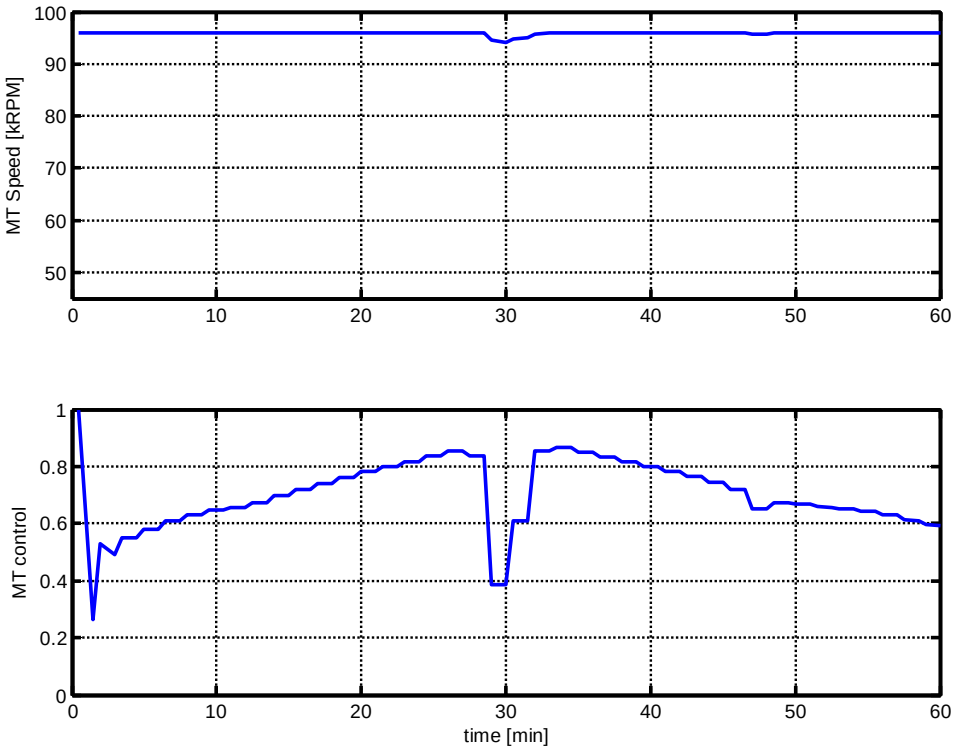

Figure 4: Turbine speed vs. normalized turbine terminal voltage.

Conclusions

A modular dynamic optimization framework for hybrid fuel cell/gas turbine power plants has been developed in AMPL and solved using IPOPT. Dynamic optimizations for dispatched load profiles were performed. This includes both increasing and decreasing ramps over the operating range. The presented results show that the developed optimization technique can control the plant as desired.

Future work will expand these optimizations to the entire operating range as well as perform ramps at various rates as well as local variations at nominal operating points. This data will be utilized in improving control strategies for FCE's ALPHA prototype of a DFC/T sub-megawatt power plant.

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References

[1] H. Ghezel-Ayagh and J. M. Daly. Progress in Development of Direct Fuel Cell/Turbine Systems. The Proceedings of 27th International Technical Conference on Coal Utilization & Fuel Systems. Clearwater, Florida, March 4-7, 2002.

[2] C. K. Weng. Robust Wide-Range Control of Electric Power Plants. Ph.D. Thesis, The Pennsylvania State University, December, 1994.

[3] A. M. Cervantes, S. Tonelli, A. Brandolin, J. A. Bandoni, and L. T. Biegler. Large-Scale Dynamic Optimization for Grade Transitions in a Low Density Polyethylene Plant. Computers and Chemical Engineering. 26:227, 2002.

[4] R. Fourer, D. Gay, and B. Kernighan, AMPL, The Scientific Press, South San Francisco,1993.

[5] A. Wächter and L.T. Biegler, On the Implementation of a Primal-Dual Interior Point Filter Line Search Algorithm for Large-Scale Nonlinear Programming, Math. Program., to appear, 2004.

[6] S. Kameswaran and L.T. Biegler, Convergence Rates for Direct Transcription of Optimal Control Problems using Collocation at Radau Points, submitted for publication, 2005.

[7] AMPL, A Mathematical Programming Language. http://www.ampl.com/index.html.

[8] S.E. Mattsson and G. Söderlind. Index Reduction in Differential-Algebraic Equations Using Dummy Derivatives. *SIAM J. Sci. Comp*. 14:677–692, 1993.